Neural Networks and Neuro-evolution

What are Neural Networks?

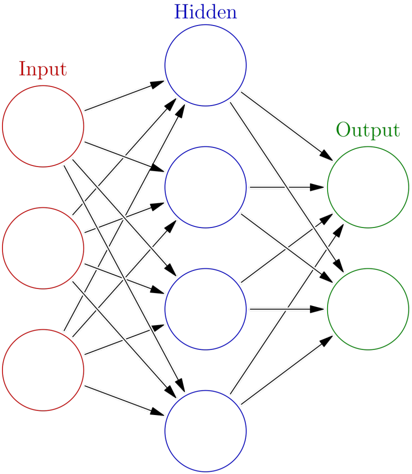
- Simplified Model of the brain
- (Connectionist Models, Parallel Distributed Processing (PDP) Models, Artificial Neural Networks)
- Highly parallel processing
- Allows learning

Many applications

- Machine learning tasks
- As useful biological models

ANNs

- ANNs incorporate the two fundamental components of biological neural nets
  - Neurons
  - Synapses



Perceptrons

- Very early models (1950s/1960s)
- “1-layer network”: one or more output units
- Output units are all linear threshold units where a unit’s inputs, x_i, are weighted with a set of weights, wi, and combined in a linear manner
- Step function computes binary output activation

Feed-forward networks

- Information flow is in one direction
- Representation is distributed
- Information processing is parallel

Backpropagation

- Requires training set (input / output pairs)
- Network is initialised with random weights
- Error is used to adjust weights

Fundamentals

- Each node has:
  - a set of input links
  - a set of output links
  - an activation function

Backpropagation

- Typically computes an output value using a simple non-linear function of the linear combination of its inputs
  - Step function: activation flips from 0 to 1 when sum is greater than threshold

$$y = \begin{cases} 0 & \text{if } \sum_{i=1}^{n} w_i x_i + b < \theta \\ 1 & \text{if } \sum_{i=1}^{n} w_i x_i + b \geq \theta \end{cases}$$

  - Sigmoid / Logistic: g(in) = 1 / (1 + exp(-in))

$$y = \frac{1}{1 + e^{-(\sum_{i=1}^{n} w_i x_i + b)}}$$

  - Rectified Linear (ReLU):

$$y = \max(0, \sum_{i=1}^{n} w_i x_i + b)$$

Advantages of NNs

- Massively parallel: Complex, global behaviour can emerge from a large collection of simple processing units
- Successful in complex tasks in a range of domains
- Robust computation: Given the distributed representation of knowledge the approach usually handles noisy and missing data

Advantages of NNs

- Gracefully degradation
- Uses inductive learning –learns from examples

Dis-advantages of NNs

- Issues with explainability
- Issues with choosing right architecture
- Open to attack

Other architectures

- Feed forward represent one (dominant) approach. However, issue exist with learning for certain problems
- Recurrent networks represent an extension on classical feedforward networks where edges from layer i can point to nodes at layer $i-1$ etc.

Common issues in training NNs

- Rate of learning?
- Overfitting
- Choosing size of neural network

Deep Learning

- Idea in computer science is not new –
- Perceptron -1950s
- Back propagation –1980s
- Convolutional NNs -1995
- ....
- Lot of hype/interest/investment/success with recent Deep Learning approaches

Deep Learning

- Big Data?-large datasets available
- Improvements in Hardware –high potential for parallelisation
- Software –wider availability of tools/frameworks (e.g TensorFlow)
- Less need to develop from scratch

Deep Learning

- Many types of problems tackled –learning sequential data, image processing etc.
- Models: Convolutional neural networks, RNNs, GANs
- Many topologies adopted.

Alternatives to Backpropagation

- Reinforcement learning (limited success)
- Artificial Evolution
  - even slower than backpropagation
  - can be used in conjunction with back propagation
  - can be used to learn more than just the weights

Neuro-evolution

- Definition: Neuro-evolution is a method of training artificial neural networks using evolutionary algorithms.
- Key Components:
  - Genetic Algorithms
  - Artificial Neural Networks (ANNs)

- Advantages:
  - Exploration of large search spaces
  - Adaptation to dynamic environments
  - Effective for complex problem domains
- Applications of Neuro-evolution:
  - Evolutionary Robotics
  - Game Playing Agents
  - Function Optimisation

Neuro-evolution Process

1. Initialization: Generate initial population of neural networks.
2. Evaluation: Assess the fitness of each network on a task.
3. Selection: Choose networks to reproduce based on fitness.
4. Reproduction: Create new networks through crossover and mutation.
5. Repeat: Iterate through generations until convergence.

Representation

- Clearly we need some way to encode a neural network as a chromosome
- Suitable approaches? Direct/indirect
- Marker based encoding

Artificial life models

- In addition to application to practical optimisation problems, the neuro evolution model has been adopted in a range of artificial life models where one can explore the interplay between population based learning (genetic algorithm), life time learning (NNs), and other forms of learning. Has led to some interesting results

Artificial life models

- Signalling
- Language evolution
- Movement behaviours
- Flocking/clustering
- Means to explore the interplay between different learning types

Artificial life - types of learning

- Population based learning - (modelleed with GAS)

Artificial life - types of learning

- Population based learning - (modelleed with GAS)
- Life time learning - (modelled with NNs)

Artificial life - types of learning

- Population based learning - (modelleed with GAS)
- Life time learning - (modelled with NNs)
- Cultural learning - (allows communication between agents)

Artificial life - Baldwin effect

- Consider a population of agents (represented by NNs) subject to evolutonary pressure (GAs)
- Many theories have been proposed to explain the evolution of traits in populations - Darwinian, Lamarckian etc
- The Baldwin Effect is a concept in evolutionary biology that suggests learned behaviors acquired by individuals during their lifetime can influence the direction of evolution.

- Baldwin Effect:
  - Learned behaviors initially arise through individual learning and are not genetically encoded.
  - Over time, individuals with adaptive learned behaviors may have higher fitness, leading to differential reproduction.
  - Selection pressures favor individuals with certain learned behaviors
  - Eventually, these once-learned behaviors may become innate or genetically predisposed in subsequent generations.
- Hinton and Nowlan experiments showing this effect

- Combining life time and evolutionary learning
  - Can evolve greater plasticity in populations -can evolve the ability to learn useful functions
  - Can be useful in changing environments
  - Allows populations to adapt
  - Examples in game play (cards, connect 4) and simulated robotics

Cultural leaning

- Allows agents to learn from each other
  - Shown to allow even greater plasticity in populations
  - Has been used in conjunction with life-team learning and population based learning
  - Has been used to model the emergence of signals, 'language', dialects

Summary

- Neural networks as learning approaches to a range of tasks (e.g classification, generation) has been successful in a range of domains (e.g. image, speech, text)
- Neuro-evolution has been shown to be useful in a range of domains
- Neural nets provide a nice model in artificial life systems